

RESEARCH ON CBR-RBR FUSION REASONING METHOD FOR ENGINEERING ANALYSIS

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ABSTRACT: The reasonable solution routine of FEM-based engineering analysis relies on specialized knowledge and experience. This paper presents a CBR-RBR fusion reasoning method to support the intelligent generation of solution routine for engineering analysis. The FEA problems were expressed as cases based on the ontology object graph. The matching of two cases was transformed into the matching between two graphs. On this basis, the author established the CBR algorithm and studied the similarity calculation method. Then, a case study was presented to validate the feasibility and effectiveness of the proposed method.

KEYWORDS: CBR-RBR fusion reasoning, engineering analysis, ontology.

1 INTRODUCTION

The finite-element method (FEM) is a popular numerical simulation tool for engineering analysis. It contains three phases: pre-processing, solving and post-processing. In general, the pre-processing phase, taking up 70~80% of the time required for the entire analysis, is fundamental to the success in problem analysis and solution. The pre-processing is further divided into geometric modelling, unit type selection, boundary condition meshing, material property definition, geometric modification, etc. In order to establish mechanical models for concrete objects in this phase, the analysts are required to thoroughly understand the physical features and working environments of the products, master the theories of mechanics and math, and have some experience in finite-element analysis (FEA) and using FEA software (Janghorban, S., 2015, Hetey, L., 2015, Miyoshi, A., 2001). The best way to fulfil these requirements lies in setting up an expert system for the FEA by artificial intelligence.

Based on fuzzy logic, Kwok, W. (2005) presented a finite-element mesh generation method that simulates the mesh design of experts and predicts the mesh size by fuzzy logic. Dolšak, B.

(2002) developed a negotiated rule-based expert system for finite-element mesh design. The system relies on machine learning method to establish a knowledge base of suitable element types and mesh sizes. Pinfold, M. (2001) designed an intelligent FEA tool for car parts. Focusing on the mesh generation mode of car parts, the FEA tool automatically generates finite-element model using the knowledge-based engineering (KBE) technology. Rao, A. (2007) created a fuzzy logic-based expert system to predict FEA results, and applied it to solve stress problems of rubber cylinder. According to the FEA features of machine tool components, Ni, X. (2005) proposed a finite-element template library, making it possible to quickly establish computer-aided engineering (CAE) FEA models of machine tool products. Zhou, X. (2001) discussed feature-based CAE modelling and feature-based intelligent post-processing techniques.

Since it is increasingly important to extract knowledge from finite-element simulation results, Guo, Y. (2009) analysed the general steps of data mining, and put forward a knowledge discovery system based on metadata and user participation. Following the data mining technology of rough set theory and principal component analysis, Ruan Xueyu et al. from Shanghai Jiao Tong University extracted calculation case and put the case into the design optimization process as a knowledge source, and successfully upgraded the CAE from the design-verification level to design-driven level (Hu, J., 2007).

Despite the above studies, it is still unknown as how to apply the analysis knowledge in simulation,

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and to achieve intelligent, efficient and standardized simulation analysis. Therefore, this paper integrates the case-based reasoning (CBR) and rule-based reasoning (RBR) to support the intelligent generation of solution routine for engineering analysis.

2 CBR-RBR FUSION REASONING MECHANISM

Existing studies have shown that it is neither effective nor natural to solve tasks with only one single reasoning algorithm. Thus, the CBR-RBR fusion reasoning method was established in this research (Figure 1).

- Input: Case features like product type, structure type, boundary dimension and analysis type etc.
- The knowledge support procedures are as follows:
- In light of the user input information, the system automatically inquires, formats and searches the case repository.

A solution should be adopted if it is both retrievable and highly consistent with the input.

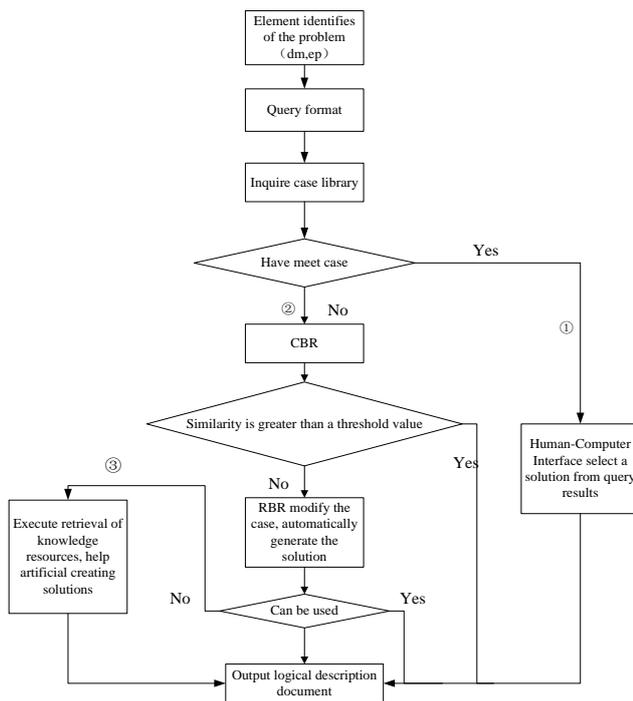


Figure 1. The CBR-RBR fusion reasoning method

In this case, the knowledge support system is equal to an FEA expert system oriented at one particular product. Therefore, the qualitative attributes analysed in previous cases can be fully reused, and the system only has to automatically adjust the value of individual quantitative parameters by the current part size, e.g. parameter

preferences. Since the analysis process, parameter types and so on have been integrated in the solutions, users only has to select the solution bearing the most resemblance to the current case structure.

In addition to model information and images, the query results should also the detailed implementation of cases. This strategy is applicable to the products with fixed structure or structure changes so minor that do not affect loads and constraints. The solutions to the same structure (e.g. gear, crank, box and carrier) in previous cases are undoubtedly reusable. The only difference between the solutions and those in the previous cases is the parameters, for the products merely have minor parametric changes.

If the perfect matching case is unavailable, Strategy 2 should be adopted: obtaining similar cases through CBR-RBR-based knowledge reasoning; with partial modifications, the current case could be made suitable for the current issue. In this process, the system automatically modifies a few qualitative parameters. The recognition of finite-element programs is essential to this stage. The engineering programs should be defined by semantic annotation in the previous cases and the FEA conditions should depicted semantically. In this way, the knowledge system is enabled to understand and analyse various problems and generate appropriate solutions, including searching for and understanding previous similar cases, and associating the information and knowledge in the model modification phase. This strategy fits in with the situation that the current case carries more or less analysis features than the previous cases.

If there is no similar case or the lack of knowledge in the knowledge base, that is, some components of the cases cannot be reasoned, the system will automatically switch to Strategy 3, and provide analysis knowledge, namely case documents, analysis parameters and a list of experts, to designers via human-computer interaction. Then, the designers should configure the solution manually based on the knowledge. In the meantime, the system will act as an analysis assistant responsible for decision support, semantic search and knowledge push. This strategy is generally used in innovative products or with the absence of corresponding template in the case base. In these circumstances, the multi-modal knowledge supporting system assists beginners and even experts in offering advices, retrieving knowledge and pushing information in view of the current context and the level of users.

- Output: semantic description document of the FEA cases. Whereas the multi-modal knowledge supporting system has to integrate various forms of expression, such as case knowledge, rule knowledge, logical knowledge and document knowledge, etc., the ontology should be adopted as the formal language of various knowledge expressions to ensure the grammatical consistency of multi-modal knowledge, and to avoid semantic ambiguity. The following key technologies must be investigated before achieving the multi-modal knowledge supporting strategy and system:
 - The CBR -RBR fusion reasoning method;
 - The knowledge retrieval method based on multi-modal semantic models.
- The two key technologies are discussed in details in the following chapters.

3 FEA SOLUTION ROUTINE MODELLING

The FEA solution routine modelling seeks to express the analysis solutions as formula cases. There are various ways of case representation, ranging from text method, attribute/value pair method to object-oriented representation. The text method describes the cases as questions and answers in free text. Specifically, the specific semantics must be understood by human intelligence; the attribute/value pair method depicts each case as a set of attribute/value pairs, and imposes a type definition constraint and a value range constraint on each attribute. The object-oriented representation fits for complex situations, and portrays each case as an object instance.

Nevertheless, these methods have some shared defects. For instance, the cases are defined in vague terms, making it impossible to explicitly express the relationship between terms in logical language, not to mention supporting logical reasoning. In this scenario, the same case is comprehended differently among different people, which adds to the difficult in integration and knowledge sharing between different case libraries and drags down reasoning efficiency. In this research, field ontology was introduced to describe the FEA cases. The theory allows formalizing different knowledge domains, so that the previous knowledge can be reused to solve problems, and achieves semantic interoperability by describing instances from different sources as cases in a unified language.

The solution route M for the engineering analysis was defined in reference to the research of Wriggers (2007). The model is expressed as:

$$M = \{QM, EC\}$$

where QM is a series of qualitative parameter description models of the object physical system, including design main model (dm), engineering problem model (ep), problem solution formalization model (ps);

EC is a group of engineering (design-analysis) cases.

For a specific physical system, the dm (ep, ps) model illustrates the constraint among the parameters of the system consisting of qualitative and quantitative parameters, and the association relationship among system components. The types and parameters of the system constitute a set of feature attributes used in the CBR process. The attributes differ in the degree of importance, denoted as W . A dm object is expressed as:

$$dm = \{nm, P, CS, CP, RL, CL, W\}$$

Where nm is the name of each component in the physical system;

P is the parameter set;

CS is the constraints/dependency set;

CP is the components/features set;

RL is the structural relationship set;

RC is the mapping from the structural relationship to the virtual components;

CL is the type of system;

W is the weight function.

The RL defines the dimension of the CP . Any structural relationship could be mapped to a virtual component of the corresponding type, and the parameters of the relationship are defined at the same time. For example, the "touch" relationship between two objects in the physical system can be mapped to the virtual components of the same "touch pair" type, which represents some major performances of the system.

The dm model, ep model and ps model maintain a many-to-many relationship, that is, a physical model corresponds to multiple engineering problems and solutions. The dm component represents the mapping from the relationship property "loadedBy" or "restrictedBy" to ep component, while the ep component is the mapping from "solveBy" to the ps component. If these models are expressed by ontology, the specific ontological concepts of model elements can be defined with semantic annotation according to the

design-analysis field ontology. An engineering analysis case ec is expressed as:

$$ec = \{cn, dm, ep, ps, V, DP\}$$

where cn is the case name;

dm describes the physical model;

ep depicts the engineering problem;

ps presents the solution;

V is a parameter set of the case (accuracy, computing cost);

DP is the dependency among dm , ep and ps . The author adopted the rule-based expression and described the modelling in the Semantic Web Rule Language (SWRL).

The dm and ep , as descriptors of the case problem, are attribute sets of case recognition, while the ps , as a section of case solution, is an attribute set that describes the solution of the case. The case ec can also be expressed as $ec = \{cn, \{dm, ep\}, ps, V, DP\}$.

For the matching between engineering problems and physical models, the similarity in physical behaviours of the case model, such as load and boundary conditions, weighs much heavier than the similarity in geometry structures. After analysing the parameters of the most similar cases, the author divided the parameters into two categories: consistent parameters and inconsistent parameters. For the consistent parameters, the parameters of the corresponding solution programs should be adopted; for the inconsistent parameters, the corresponding solution parameters should be determined through the RBR and confirmed via the human-computer interaction.

The analysis rules can be described as:

$$P \rightarrow Q \text{ or } P \text{ then } Q.$$

Where P is the precondition used to identify the available conditions; Q is a set of conclusions or operations under the precondition P .

The meaning of the production goes: if the precondition P is fulfilled, then the conclusion Q can be drawn or the operation Q should be executed.

For the sake of knowledge sharing and integration, the author made formal expression of analysis rule by ontology. As mentioned above, the OWL-DL provides complete definitions of concepts and classifications, and enough axioms on type operation, but fails to achieve the RBR. Therefore, this paper attempts to describe the analysis rule in the SWRL.

4 THE CBR-RBR FUSION REASONING ALGORITHM

In this research, the system mainly relies on a fusion reasoning mechanism that combines the CBR and the RBR. According to the original design conditions and requirements, the CBR was adopted for reasoning in the design phase, during which the previous case template was retrieved by analogy, and the closest analysis solution model was extracted. After pinpointing the similarities and differences, the RBR was employed to modify the model for the differences, including unit type selection, meshing control and calculation method selection, etc.

Under the framework of multi-modal knowledge supporting system, the following ontology-based CBR-RBR fusion reasoning algorithm was presented for the domain model M :

The CBR algorithm:

- Object graph building: search algorithm (matching algorithm). The case is represented as two graphs ($G1$ and $G2$) consisting of nodes and directed edges, turning the CBR-based similarity assessment of the two cases into the assessment of the two graphs. Whereas such an NP problem cannot be resolved directly, the following strategy should be taken: First, simplify the object graph by extracting the nodes in associative side, establish a mapping relationship between the sets of nodes/edges $G1$ to $G2$, and then calculate the similarity in the mapping relations between the two nodes/edges.
- Similarity assessment: the ontology-based method should be adopted to calculate the concept of CL (mainly calculate this value) between mapping nodes/edges, and compute the partial semantic similarity of property RL and property value P , thereby concluding the overall semantic similarity of the case tree G .
- RBR-based case adjustment algorithm: modify the most similar retrieved case and generate an appropriate FEA analysis solution for the current case.

The algorithm is implemented in the following steps:

Step1: Query for the format.

Step2: Obtain a case set of the same kind of analysis problems based on the query requirement, and prepare for calculating the case similarity.

Step3: Establish two trees representing two instances.

Step4: Establish the mapping between two trees in the corresponding nodes (Zhang, P., 2003).

Step5: Calculate the local semantic similarity of the concept CL (mainly calculate this value; if the similarity value exceeds the threshold, calculate the similarity of back relationship and attribute values. This saves the time for low similarity case calculation), property RL and property value P between mapping nodes, and the overall semantic similarity of this node (Pan, X., 2005, Mei, X., 2007).

Step 6: Repeat the above steps until all the trees are traversed.

Step 7: Calculate the similarity of trees.

Step 8: Compare the values of case similarity and threshold.

Step 9: Continue with the search and calculation if the goal is not satisfied.

Step 10: Carry on with the RBR case adjustment if the goal is satisfied (Jiang, L., 2009).

5 A CASE STUDY

The physical system of the current case is the box component shown in Figure 2a.

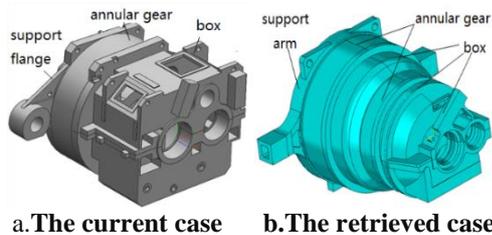


Figure 2. The physical models of the current case and the retrieved case

The system was analysed in the static FEM. As mentioned above, the CBR system constructed the case tree based on the inputted case features, calculated the similarity according to the concept hierarchy of domain ontology and feature description, and identified the most similar case: an 1.5MW wind turbine gearbox component with a two-stage planetary gear system and a fixed axis (Figure 2b). The case was modified by the RBR algorithm, and the resulting parameters are shown in Table 1.

Table 1. The main component parameters of the generated solution

Characteristics	Parameters	Values
1.5_1_2_SubAss embly	CAE system	ANSYS
	Material model	Linear elastic
	Problem type	STATIC
	FE type	SOLID95

Ear1, Ear2	Restriction type	Stiff
	Direction	All directions

InternalGear1	Load type	Moment

BearingHoleC, BearingHoleF	Load type	AxialBearingForce

BearingHoleA, BearingHoleB, BearingHoleD, BearingHoleE, BearingHoleO, BearingHoleG BearingHoleN	Load type	RadialBearingLoad
	Distribution Mode	Cosine
	RegionAng	120

BearingHoleH	Load type	AxialBearingForce RadialBearingLoad
	Distribution Mode	Cosine
	RegionAng	120
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6 CONCLUDING REMARKS

After analysing the knowledge diversity featuring in the FEA solution development, the author proposed the multi-modal knowledge supporting strategy for the FEA program. The concept of ontology object graph was introduced to convert the matching of two cases into the matching between two graphs. Then, the CBR algorithm was established, and the similarity calculation method was studied to improve the sharing and reusability of the case library. On this basis, the RBR was adopted to guide case correction and the case correction algorithm was created based on ontology and the RBR. Considering the man-made influence on intelligent activities, the semantic retrieval mechanism was established to help designers with efficient positioning of the knowledge resources required for the FEA program. The multi-modal knowledge supporting method was made more adaptable and flexible through the human-computer interaction.

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8 REFERENCES

- Dolšák, B. (2002). *The finite element mesh design expert system*, Knowledge-Based Systems, 15(5): 315-322.
- Guo, Y., Wang, J., Ling W. (2009). *Study on knowledge discovery system based on result of finite element analysis*, Manufacturing Automation, 31(9): 175-178.
- Hetey, L. (2015). *Advisory system development for reliable fem modelling in aerospace*, Aircraft Engineering & Aerospace Technology, 87(1): 11-18.
- Hu, J., Peng, Y., Li, D., Yin, J. (2007). *Robust optimization based on knowledge discovery from metal forming simulation*, Journal of Materials Processing Technology, 187: 698-701.
- Janghorban, S., Wang, Q., Holmes, D. G. (2015). *A knowledge-based magnetic component design system with finite element analysis integration[C]// Apec.*
- Jiang, L. (2009). *Semantic Web Technology Based Study on Mechanical Design Methods and Techniques*, Dalian: Dalian University of Technology.
- Kwok, W., Haghghi, K. (2005). *A Fuzzy Logic Knowledge-Based Approach for Finite Element Mesh Generation and Analysis*, Journal of Computing and Information Science in Engineering, 5: 317-329.
- Mei, X., Meng, X., Chen, J., Xu, M. (2007). *SSCM: an scheme for calculating semantic similarity*, Chinese High Technology Letters, 17(5): 458-463.
- Miyoshi, A., Yagawa, G., Shimizu, R., Tamura, T., & Sasaki, S. (2001). *An interface agent system for cae*, Jsme International Journal, 44: 623-630.
- Ni, X., Yi, H., Ni Z., Tang W. (2005). *Research on the expert system for FEA of machine tool's components*, Journal of Southeast University (Natural Science Edition), 35(2): 211-215.
- Pan, X. (2005). *The Research on Key Technologies of the Context Integrated Knowledge Management*, Hangzhou: Zhejiang University.
- Pinfold, M., Chapman, C. (2001). *The application of KBE techniques to the FE model creation of an automotive body structure*, Computers In Industry, 44(1): 1-10.
- Rao, A., Pratihari, D. (2007). *Fuzzy logic-based expert system to predict the results of finite element analysis*, Knowledge-Based Systems, 20(1): 37-50.
- Wriggers, P., Siplivaya, M., Joukova, I., Slivin, R. (2008). *Intelligent support of the preprocessing stage of engineering analysis using case-based reasoning*, Engineering with Computers, 24(4): 383-404.
- Zhang, P., Wang, W., Yu, W. (2003). *The Object-Graph Based Case Representation Paradigm And Its Similarity Metrics*, Proceedings of The Chinese Society For Electrical Engineering, 23(12): 59-63.
- Zhou, X., Yu, C. (2001). *System Integration Forming Engineering for Stamping CAD and CAE*, Journal of Shanghai Jiaotong University, 35(10): 1501-1505.